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Local droughts and income risk among Thai households

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Abstract

This paper investigates the extent to which households in rural Thailand across the income distribution are able to mitigate income risks in the face of shocks. It uses especially high-quality household income and consumption data spanning 64 Thai villages over 15 years. The paper identifies income shocks by village-level variations during drought conditions. It finds that richer households are better able to mitigate income risk than poorer households, in contrast to some studies of the South Asian subcontinent. These possibilities for managing income risk are shown to be correlated with the type of contract the head of household is likely to be employed in, the share of salaries in total household income, the education level of the head, the relative youth of the heads of richer households, and location effects.

KEYWORDS

inequality, poverty, risk, Southeast Asia, Thailand

JEL CLASSIFICATION

O12; O15; D15; D31; I32

1 | INTRODUCTION

In low- and middle-income countries access to credit markets may be incomplete, especially for poor or rural households. These households may therefore have an incentive to insure their consumption levels by obtaining their income from less-volatile sources or by diversifying their income sources. In an influential pair of papers, Morduch (1994, 1995) used the term "income smoothing" to describe this phenomenon and contrasted it with "consumption smoothing" that is commonly observed in richer countries. A number of papers have documented low-risk income strategies among the relatively poor in rural communities of low-income countries. Morduch (1995) presents evidence that asset-poor households in rural India, whose consumption is most vulnerable to income shocks, devote a greater proportion of their land to safer but lower-yielding traditional varieties of crops than richer households. Rosenzweig and Binswanger (1993) demonstrated that rural Indian households in lower-wealth quartiles used production techniques that were less susceptible to rainfall variation, even though on average these techniques were less productive. Kochar (1999) found that when faced with crop failure, such households protected their consumption levels by diverting labor from farm employment to off-farm employment, thereby reducing income variability by diversification rather than smoothing consumption directly through borrowing or dissaving. More recently, using data from Mexico, Gutierrez (2014) extends the analysis of income smoothing to implicit contracts that reallocate risk from formal salaried workers to their employers in middle-income countries.

However, another strand of the literature has observed that poorer households may be constrained in their ability to enter low-risk income-generating activities. Dercon and Krishnan (1996) find that in rural Ethiopia and Tanzania, poorer households lack the lumpy assets required to enter high-return, low-risk activities (e.g., cattle rearing or shopkeeping). They also find that low levels of education restrict the ability of relatively poor households to gain low-risk salaried employment. Dercon (2002) surveys the various constraints to effective risk management faced by poor households.

If this last evidence is general, then although richer households are less likely to be liquidity constrained and therefore *less in need* of insuring themselves through smooth income, they may have privileged access to low-risk income streams and therefore be *more able* to manage income risk. It is then an empirical question as to whether richer households are more likely to utilize low-risk incomes to satisfy their insurance needs than their poorer counterparts. The present paper examines this empirical question of the distributional impact of low-risk income opportunities using a long running panel of high-quality household surveys from rural Thailand (see Townsend, 2011) spanning 64 villages over 15 years from 1997 to 2011.

To distinguish between relatively rich and relatively poor households, I compute observed "permanent income" for each household. From Friedman (1957), I take the average over time of real, equivalized consumption for each household in the 15 years for which I have data as a proxy for permanent income. I show that consumption volatility as measured by the standard deviation of real, equivalized consumption is largely constant over the distribution of permanent income, but a similarly constructed measure of income volatility declines systematically with permanent income. These findings are not consistent with models of income risk that predict that low-income households will rely more heavily on low-volatility income (as in Morduch, 1994). Rather, they lend support to Dercon and Krishnan's (1996) hypothesis that poorer households may be excluded from low-risk income opportunities.

The paper adopts a formalized model of the income-generating process of households where income comprises a long-term component and a transitory, stochastic component (as in any number of studies of consumption smoothing, including Friedman, 1957; Hall, 1978). In formal empirical modeling, I follow Paxson (1992) and further decompose transient income into a village-wide component and a household-specific component. I use information gathered by the Townsend Thai Project from key informant interviews with village headmen to compute the proportion of households in each village affected by a drought in 14 of the survey years and use this as a source of exogenous variation in transient income of all households surveyed within that village cluster.

The empirical section of this paper tests for differences in the extent to which the income streams of individual households are insured against the cluster-level prevalence of drought by the level of household permanent income. The identifying assumption is that in the absence of differences in risk management strategies, covariate shocks would have had the same proportionate effect on household incomes across the income distribution within each cluster, on average. I find that the income streams of relatively rich households are indeed less sensitive to this covariate shock than their poorer counterparts. This result is robust to a specification that allows for endogenous household responses to income shocks, such as added worker effects and labor displacement to alternative activities. The paper also conducts sensitivity analysis and finds that the result is robust to a range of specifications that split the sample into relatively rich and relatively poor households at the 40th, 50th, and 60th percentiles; to the inclusion of village (as opposed to household) fixed effects; to the inclusion of household random effects; and to the inclusion of linear and quadratic region-specific time trends. Quantile regressions also confirm that the income streams of the richest households are insulated against drought, whereas the rest of the distribution suffer significant losses due to this source of risk.

To identify the constraints that prevent poorer households from accessing low-risk income streams, the paper tests for heterogeneity in the effect of drought on household transient income by different household characteristics. Testing at the 5% level reveals that drought does not exert a statistically significant effect on the income streams of households that have access to salaried jobs that pay steady monthly wages, on households that are headed by people who are highly educated or from younger cohorts, or on households from the relatively affluent central region. These results are consistent with Dercon and Krishnan's (1996) view where relatively poor households are constrained in their ability to secure low-risk income by factors such as human capital and location. They also provide complementary evidence to Gutierrez's (2014) result that salaried employment in middle-income countries serves an important, though under-researched, role in reducing income risk.

Heterogeneity analysis also reveals that some of the channels through which income-risk management takes place in poorer, more agrarian settings (e.g., those studied by Dercon & Krishnan, 1996; Kochar, 1999; Morduch, 1994, 1995; Rosenzweig & Binswanger, 1993) may not be as vital in middle-income countries. In particular, I find no evidence that differences in crop portfolios, holdings of large livestock, business ownership, and the presence of additional breadwinners in the household drive the observed differences in income risk across the distribution.

The rest of the paper is organized as follows. Section 2 reviews the literature that this paper builds on. Section 3 describes the data from the Townsend Thai Project. Section 4 presents some descriptive evidence that richer households depend more heavily on low-risk income to satisfy their insurance needs than poorer ones, in contrast to the findings of earlier studies of rural India. Section 5 presents the main empirical results of this paper while Section 6 concludes.

2 | LITERATURE REVIEW

2.1 | Liquidity constraints, insurance, and low-risk income

In economies where households have access to well-functioning capital markets, even risk-averse households are likely to make production decisions that maximize the mean of income (even though this usually implies a higher variance) and use borrowing and lending to smooth consumption against the resulting risk in their income streams (Fisher, 1930). A number of studies have documented the extent of consumption smoothing in the Thai panel (e.g., Alem & Townsend, 2014; Gine & Townsend, 2004; Paulson & Townsend, 2004). However, studies of this panel have also yielded clear evidence that households are liquidity constrained (most notably Kaboski & Townsend, 2005, 2012) so that the degree to which consumption is smoothed is imperfect.

Credit constraints imply that even a temporary income fluctuation can provoke a decrease in consumption levels (Deaton, 1991) so that risk-averse households may prefer lower-risk income streams, even at the expense of a lower mean. Morduch (1994) formalizes this decision as a portfolio choice problem where households can choose the share of income generated using a risk-free technology and a risky technology that has a higher mean return. He shows that the optimal share of income generated using the risk-free asset is greater when the household is liquidity constrained than when it is not.

Much of the empirical evidence in this literature has been informed by household-level data on Indian villages gathered by the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT). Morduch (1995) presents evidence that asset-poor households, whose consumption is most vulnerable to income shocks, devote a greater proportion of their land to safer, but lower-yielding, traditional varieties of crops than richer households. Also using the ICRISAT data, Rosenzweig and Binswanger (1993) demonstrate that Indian households in lower-wealth quartiles choose agricultural input combinations which are less susceptible to rainfall variability but also return a substantially lower yield. Rosenzweig and Stark (1989) show that Indian marriage migration serves to reduce fluctuations in income and thereby consumption. Using the same data, Kochar (1999) finds that when faced with crop failure, poor households that cannot protect consumption by borrowing divert labor from farm employment to off-farm employment, thereby mitigating variation in their income streams. In the first study of income smoothing in a middle-income country that I am aware of, Gutierrez (2014) identifies the insurance function served by salaried employment. The present paper contributes to this emerging strand of the literature by presenting further evidence on the distribution of income risk from a middle-income context with a set of village households at a relatively advanced stage of economic development and more diversified income activities.

Strategies to manage income risk can have far-reaching implications for a range of important economic issues. If these strategies are effective at providing some degree of insurance, the welfare loss associated with the absence of markets for insurance and credit will be relatively small (Morduch, 1995). As smoother income typically implies a lower mean, a widespread reliance on this insurance strategy may cause economy-wide output to be lower than it would otherwise be (Morduch, 1995). If income smoothing is concentrated at the lower quantiles of the income distribution, income inequality will be exacerbated over time (Rosenzweig & Binswanger, 1993, p. 98). It may also affect poverty as relatively low mean incomes are likely to be an impediment to asset accumulation and may leave households in a poverty trap (Carter & Barrett, 2006; Dercon, 2006).

2.2 | Constrained income choice

Dercon and Krishnan (1996) present evidence that, notwithstanding liquidity constraints, poorer households in Ethiopia and Tanzania are also constrained in their ability to access high-return income-earning activities. In their sample, cattle rearing and, in some cases, shopkeeping are associated with higher consumption and asset accumulation. The authors find evidence that poorer households are excluded from entering these activities because they require lumpy, up-front investments. They identify liquidity constraints, small farm size, lack of male labor within the household, and geographic location as factors that prevent poorer households from entering these high-return activities. Instead, poorer households are restricted to taking up low-return off-farm activities, such as collecting firewood, that do not require up-front entry costs.

Many of these forces are also salient to villages sampled by the Townsend Thai Project, which also exhibit important regional differences (Pawasutipaisit & Townsend, 2011; Samphantharak & Townsend, 2018; Townsend, 2013). The present paper will show that this geographical variation also extends to the availability of low-risk income opportunities to the exclusion of households from the poorer northeastern region, thereby generalizing Dercon and Krishnan's (1996) result from developing countries to a middle-income country. These results complement the predictions of Felkner et al. (2009) who based on monthly data from a smaller sample of Thai households predict that poorer households will be less able to adapt to rainfall shortages in a high-warming climate-change scenario.

These forces motivate the key research questions of this paper. First, does the degree of income risk differ across the income distribution? Second, are differences in the observable characteristics of households empirically related to these differences in income risk?

3 | DATA AND DESCRIPTIVE STATISTICS

3.1 | Income and consumption in the annual series of the Townsend Thai Project

This paper uses data collected and made publicly available by the Townsend Thai Project. This project has been collecting household data from a large number of Thai villages on a continuous, annual basis from 1997. The project has also been collecting monthly data from a smaller sample of households from 1998. From 2006 it fielded further annual surveys in urban areas. As this data series has already been used in a wide variety of highly regarded and well-known empirical work, I discuss only those aspects of the data that are immediately relevant to this paper. For interested readers, Townsend (2016) provides an accessible and detailed account of the data collection project as well as an overview of the numerous contributions that these data have yielded.

The current paper is based on the annual series of rural household surveys that have been fielded in 64 villages every year from 1997 to 2011. Each year, 960 households are sampled across these 64 villages. Because I am interested in the dynamics of the income and consumption streams of these households, I focus on the balanced panel of 609 households who do not report missing, negative, or obviously spurious values for income or consumption in any period so as not to conflate the dynamics under analysis with the entry and exit of households to and from the panel.[1]

The key outcome variable in this paper is net household income measured in Thai Baht. This is computed by subtracting agricultural and business expenses from gross household income in the 12 months preceding the survey. Production for home consumption is included in this aggregate at self-reported market prices for home-produced goods. Unpaid family labor is not included in the income aggregate, though as mentioned, the value of the goods they contribute to the production of is. These numbers are adjusted for inflation to 2011 prices using Bank of Thailand data and equivalized using the “old OECD Scale” (OECD, 1982).[2] The summary statistics for the resulting income data by each year for the balanced panel of 609 households are presented in panel A of Table 1. Unsurprisingly, there is evidence of strong growth in real income among these Thai villages over the sample period (with the only major year-on-year reduction in mean income occurring in the aftermath of the 1997 East Asian financial crisis).

In addition to the income aggregate discussed earlier, the Townsend Thai Project collects disaggregated income data. To convey a sense of the relative importance of the different components of household income, panel B of Table 1 presents gross income disaggregated by farm income (which includes agriculture, livestock rearing, and fisheries), business income (including income from shops, mills, trading activities, and other businesses), salary income, and income from other sources. Disaggregated in this way, it is apparent that the sampled communities continue to be largely agricultural households,

TABLE 1 Descriptive statistics

Variable	*N*	Mean	Standard deviation	Minimum	Maximum
Panel A: real, equivalized net income by year (2011 prices)					
1997	609	38,976	61,995	185	659,758
1998	609	35,981	48,734	543	522,935
1999	609	34,384	43,445	246	548,633
2000	609	35,761	44,528	992	554,685
2001	609	39,195	52,440	2,247	647,944
2002	609	39,110	45,011	1,357	414,579
2003	609	45,676	53,761	1,555	629,592
2004	609	48,358	81,091	515	1,607,585
2005	609	50,195	94,417	175	1,596,179
2006	609	46,984	67,897	876	1,195,125
2007	609	57,324	106,566	2,466	1,956,726
2008	609	55,675	57,909	1,154	597,982
2009	609	66,446	89,091	2,822	1,262,184
2010	609	71,569	84,426	5,309	959,973
2011	609	77,021	75,524	8,000	647,629
Panel B: pooled real income components					
Equivalized net income	9,135	49,510	71,087	175	1,956,726
Gross farm income	9,135	69,817	168,358	0	3,263,781
Gross business income	9,135	31,705	207,599	0	5,878,242
Gross salary income	9,135	26,006	85,313	0	1,311,897
Gross other income	9,135	49,518	92,549	0	3,759,456
Panel C: real equivalized consumption (2011 prices)					
By year					
1997	609	27,323	31,627	2,172	318,781
1998	609	21,277	30,480	2,158	667,738
1999	609	18,421	17,337	1,479	187,560
2000	609	17,549	18,927	568	209,664
2001	609	17,161	16,110	466	148,964
2002	609	17,687	19,996	1,745	286,213
2003	609	17,972	19,465	1,031	282,283
2004	609	19,815	22,571	2,123	279,047
2005	609	21,218	22,307	3,338	233,545
2006	609	22,047	26,960	3,470	312,806
2007	609	21,810	22,323	3,920	242,977

(Continues)

TABLE 1 (Continued)

Variable	*N*	Mean	Standard deviation	Minimum	Maximum
2008	609	21,167	17,268	3,188	164,158
2009	609	23,296	24,795	4,630	399,249
2010	609	24,835	19,672	4,360	254,372
2011	609	25,338	22,955	2,300	362,094
Pooled consumption	9,135	21,128	22,817	466	667,738
Panel D: key informant data (pooled)					
Drought-affected households	1,024	28	68	0	1,306
Total households in village	1,024	180	305	21	3,250

Notes: Adjusted for inflation using Bank of Thailand Data. 31.51 Thai Baht = US$1 on December 31, 2011 (*source*: exchangerates.org.uk). Business, farm, salary, and other income components reported here are adjusted for inflation but not equivalized. Net income and consumption figures are equivalized using the "Old OECD" (OECD, 1982) scale.

with agriculture comprising the single-largest source of income followed by business income and salary income.

Panel C of Table 1 presents analogous summary statistics for household consumption (inclusive of the consumption of goods produced at home). With the exception of the East Asian financial crisis of 1997 and the great recession of 2008, real consumption tends to grow over the duration of the sample. This consumption variable is constructed from two distinct parts of the questionnaire: annual consumption items and monthly consumption items. The annual consumption items include spending on household and vehicle repairs, education, clothing, and eating outside the home. Monthly consumption items include various food items, gasoline, alcohol, and tobacco as well as expenditure on rituals. Production for home consumption is also included in this aggregate. To make these data sources comparable, the expenditure on monthly items is multiplied by 12 and added to the annual expenditure items to form the consumption aggregate. The resulting consumption variable is then inflated to 2011 prices and equivalized using the old OECD scale before analysis. The final row of panel C shows the summary statistics for real, equivalized consumption pooled over the entire panel. This consumption measure does not include durable goods such as televisions, motor vehicles, and refrigerators, which are instead included in the measure of household assets. As a result, pooled average (nondurable) consumption is noticeably less than pooled average income. Consumption is also considerably less volatile than income as households in this setting have been shown to pool income risk (Chiappori et al., 2013, 2014) and to smooth consumption over time against shocks to income, albeit imperfectly (Kaboski & Townsend, 2005; Townsend, 2016).

3.2 | Shocks

To identify differences in the degree to which the income streams of different households are insured, I require variables that exogenously affect household income prospects. A standard approach uses adverse weather shocks (Dercon, 2004; Kochar, 1999; Rosenzweig & Binswanger, 1993). These studies have used meteorological data on rainfall variation. However, the villages used for the current study are drawn from relatively tightly packed geographic units in central and northeastern Thailand (Townsend, 2016) so that rainfall data cells are unlikely to exhibit sufficient variation between villages to be useful. Furthermore, exact village geo-locations (which are necessary to effectively utilize rainfall data) are not made publicly available by the Townsend Thai Project. Rather, the project collects information on the occurrence and incidence of adverse weather shocks by interviews with a village "key informant," who is typically the village headman. Each year from 1998 to 2011 (i.e., with the exception of the first year for which household data are available), a key informant reports the number of households affected by drought in each village and the total number of village households.[3] Panel D of Table 1 presents the relevant summary statistics for the 64 villages spanning 14 years. On average, 28 households per village are affected by drought in any given year, whereas the mean village size is 180 households.

Though the aforementioned descriptive statistics evidence substantial variation in the incidence of drought, they conflate intervillage and intertemporal variation. Figures 1 and 2 provide a better sense of the distribution of the drought over time and across villages. For each year, Figure 1 plots the average over the 64 sample villages of the share of households affected by drought. The worst

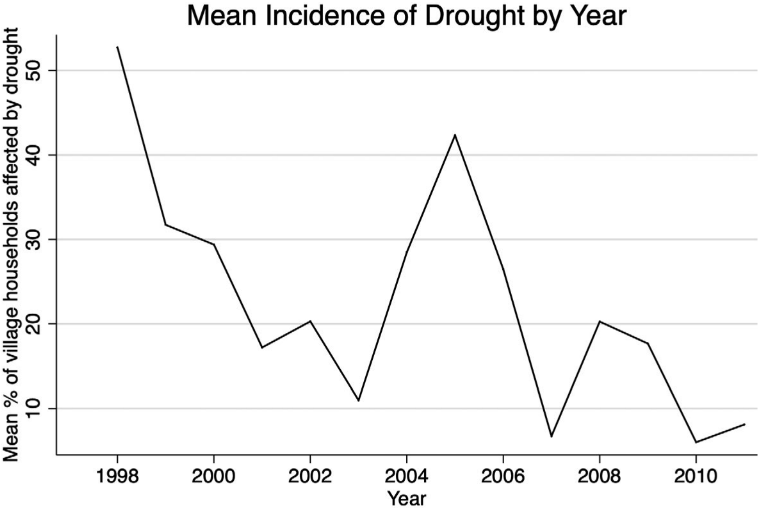

FIGURE 1 Mean incidence of drought by year

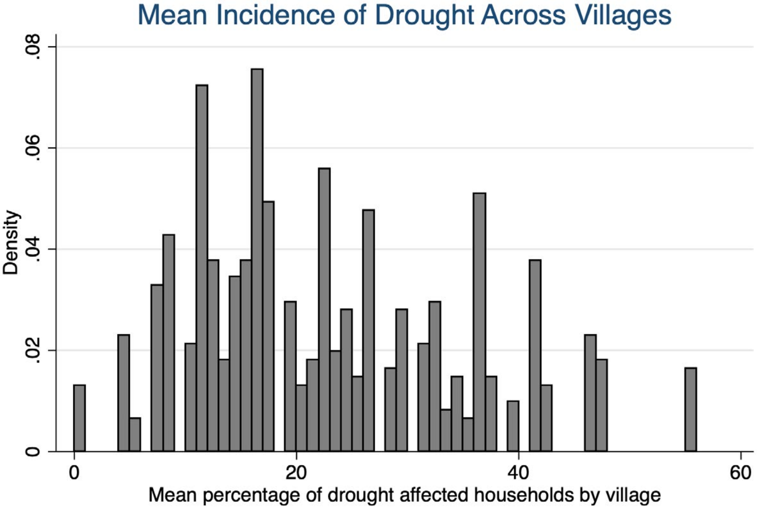

FIGURE 2 Mean incidence of drought across villages

year on record is 1998 where the average share of households affected by drought in these areas was 52.7%. The year in which the average share of households affected by drought was at its lowest value of just over 6% was 2010. In contrast to Figure 1 that allowed us to get a sense of variation across time, Figure 2 is intended to provide a sense of the extent to which the incidence of drought varies across villages. Here, for each village I have computed the average over time of the share of households affected by drought and plotted a histogram of the resulting densities. In the village that is least affected by drought, the average share of households affected is 0.4%, so there are no villages in the sample that are completely unaffected by drought for the whole duration of the panel. At the other extreme, the average share of households affected by drought in the worst-affected village is 55.3%. Thus, the incidence of drought exhibits substantial variation both over time and across villages. Furthermore, when a village does experience a drought, a large proportion of the households within that village are usually affected. The mean of the share of village households affected by a drought conditional on the village experiencing a drought in a given year is 51.9%. These features of the distribution of drought recommend its use as an exogenous, covariate shock to the income streams of village households.

4 | THE DISTRIBUTIONS OF CONSUMPTION RISK, INCOME RISK, AND HOUSEHOLD CHARACTERISTICS

As preliminary evidence, Figures 3–5 study the distribution of income risk and consumption risk across households. The analysis underlying these figures does not assume a specific source of risk, nor does it restrict attention to adverse shocks. Rather, it uses observed variation in household income and consumption over time—specifically the standard deviation of the log of real, equivalized household income and consumption—to measure the exposure to risk. Income risk, measured in this way, is the net of any ex ante smoothing mechanisms adopted by the household, whereas consumption risk is the net of all smoothing achieved by the household such as through saving, dissaving, and informal payments to and from kinship networks.

The variable on the x-axis of these figures is the observed level of "permanent income" for each of the 609 households in the balanced panel, with permanent income as defined previously. Temporary fluctuations in income and measurement error will cause any ranking of households based on the

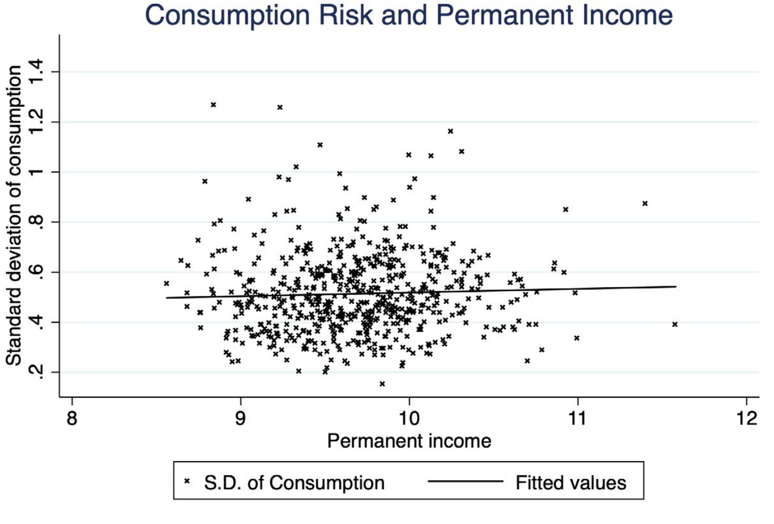

FIGURE 3 Consumption risk and permanent income

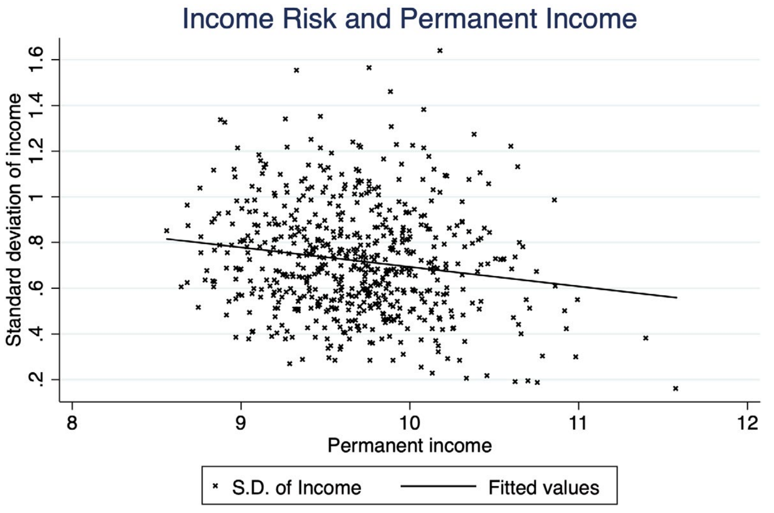

FIGURE 4 Income risk and permanent income

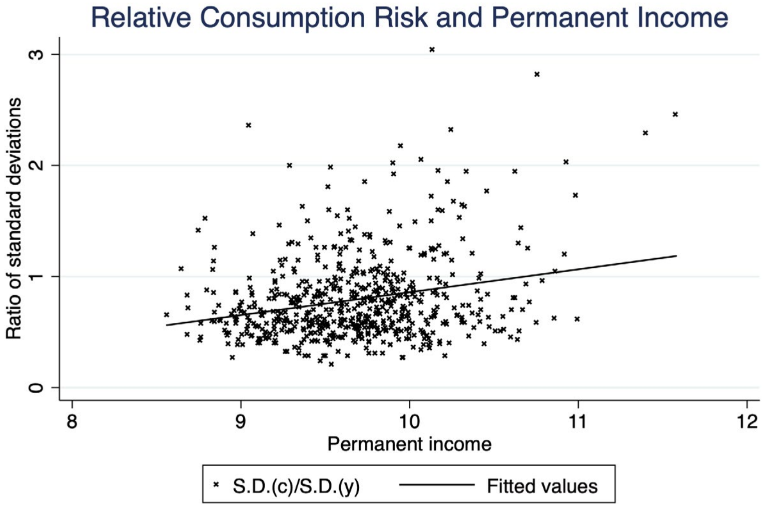

FIGURE 5 Relative consumption risk and permanent income

level of income in a particular period to be an unreliable measure of underlying relative well-being. Averaging over observed incomes for the duration of the panel partially addresses this concern, though such an average may continue to provide a misleading impression of relative well-being if households are at different stages of the life cycle, as households headed by retirees may consume out of savings or transfers rather than income and may therefore enjoy systematically higher well-being than their incomes indicate. In the permanent income view (Ando & Modigliani, 1963; Friedman, 1957), averaging over consumption will be a more reliable signal of permanent income. Therefore, the x-axis of these figures uses the average over time of real, equivalized consumption of each of these households as a proxy for "permanent income."

To provide the reader a sense of the magnitude of these variables, I note here that the sample average (the mean and median are identical to three significant figures) of permanent incomes computed in this method is 9.68, whereas the mean adult equivalent in a sample household is 3.06 so that the sample average household consumed ~48,900 Thai baht at 2011 prices. This equates to ~US$1,550 per household without adjusting for purchasing power parity. At the 25th percentile of the income distribution, I observe a permanent income of 9.37, which following a similar calculation corresponds to an annual household income of 35,900 baht or US$1,140. Permanent income at the 75th percentile is 9.96 corresponding to an annual household income of 64,800 baht or US$2,100.

To validate mean consumption as a measure of permanent income, I plot it against a similarly constructed measure of mean income in Figure 6. The figure shows a strong, positive relationship between the two variables. A univariate linear regression confirms that the mean income explains 66% of the variation in mean consumption and yields a resounding rejection of the null hypothesis that mean income is independent of mean consumption (*t*-statistics: 34.5).

Returning to Figure 3, the *y*-axis measures the sample standard deviation in the log of each individual household's real, equivalized level of consumption over the 15 years of the panel, $\widehat{\sigma}_c$. This is a crude measure of the extent to which the consumption streams of these households exhibit a lack of insurance after the household has deployed the consumption smoothing mechanisms available to it. The figure plots this measure of consumption variability against the measure of permanent income for the 609 households that comprise the balanced panel in the annual series of the Townsend Thai data. The line of best fit through these points suggests (and a *t*-test reported in the first column of Table 2 confirms) that the degree of insurance does not differ significantly across the spectrum of household permanent income.

Figure 4 plots the sample standard deviation of log income, $\widehat{\sigma}_y$, against mean consumption for the same 609 households. Here there is a clear downward trend, the coefficient for which is presented in the second column of Table 2. Thus, relatively well-off households have significantly smoother income streams than their worse-off counterparts. While the possibility that differences in measurement error affect these results cannot be ruled out, it is worth noting that typically measurement error in income tends to be greater at the higher end of the income distribution. If this is true of the Thai data,

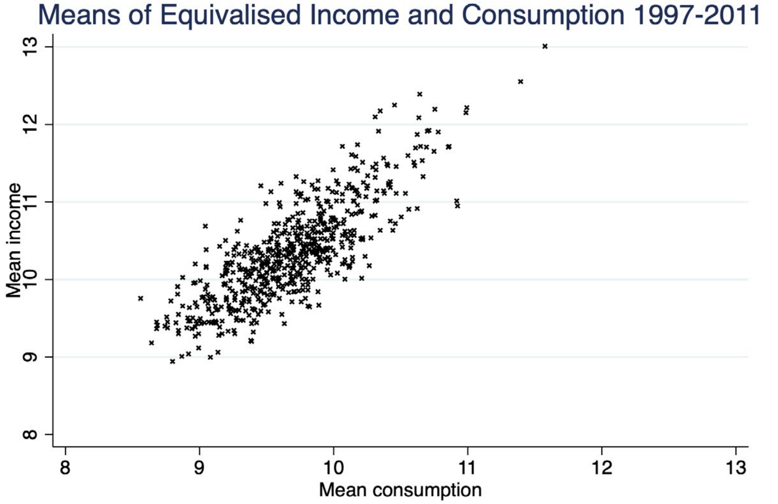

FIGURE 6 Means of equivalized income and consumption 1997–2011

TABLE 2 Income smoothing and consumption smoothing

	(1)	(2)	(3)	(4)	(5)
Dependent variable	***SD*(c)**	***SD*(y)**	***SD*(c)/*SD*(y)**	**CV(c)/CV(y)**	***SD*(f)/*SD*(y)**
Mean	0.0147	−0.0852***	0.206***	0.227***	0.0906***
Consumption	(1.02)	(−4.06)	(6.21)	(6.21)	(2.81)
Constant	0.372***	1.545***	−1.201***	−1.349***	0.0296
	(2.65)	(7.60)	(−3.73)	(−3.8)	(0.14)
N	609	609	609	609	609

Notes: SD(c) is the standard deviation of real, equivalized, nondurable consumption for each household over the duration of the panel. *SD*(y) is the standard deviation of real, equivalized net household income. *SD*(f) is the real, equivalized standard deviation for food, alcohol, tobacco, and fuel consumption. CV is the coefficient of variation. Mean consumption is the mean of real, equivalized household consumption over the 15-year duration of the panel, an empirical proxy for household permanent income. *t*-Statistics are in parentheses.

$^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

then measurement error would bias the coefficient upward so that the true coefficient would be even more negative than this estimate.

I now compute the ratio $\widehat{\sigma}_c/\widehat{\sigma}_y$ to gauge the extent to which consumption is smoothed relative to income. Figure 5 plots the estimates of this consumption smoothing measure against mean household consumption. The proportion of income variation that is allowed by households to pass uninsured into consumption variation increases with the level of mean consumption. Poorer households smooth consumption more, relative to income, whereas better-off households seem to achieve the same degree of net smoothing in their consumption stream (from Figure 3) by relying more heavily on low-variance income. These patterns are robust to an alternative measure of variability, namely the coefficient of variation (Table 2, column 4), and to a more restrictive definition of consumption that includes only food, alcohol, tobacco, and gasoline expenditure but excludes expenditure on rituals, clothing, repair of durable goods, and homestead repairs (Table 2, column 5).

These patterns of income and consumption risk are at odds with theories of income smoothing that highlight the role of credit constraints and so find that the poor are more likely to seek low-risk income as insurance. A possible explanation may lie in theories of constrained income choice that find that the poor are less able to access low-risk income because of specific observable characteristics.

Table 3 assesses whether the observable characteristics of households differ by the level of permanent income by dividing the sample into two groups. Households with permanent income above the median are significantly more likely to be headed by people who are in government work, other jobs that pay steady monthly salaries, or business, as opposed to varying daily wages, piece rates, or unpaid family work. The heads of these richer households are also, on average, younger, better educated, more likely to have more than one source of income, and more likely to be male. These richer households are less likely to be dependent on a sole breadwinner and slightly *more* likely to report being "involved in agriculture." Despite this last statistic, the analysis of the income portfolio weights in the final three rows of Table 3 shows that poorer households derive a greater share of their income from rice (the main crop),[4] and (to a lesser extent) livestock such as pig, cow, and buffalo, in contrast to richer households that derive a greater share of their income from salaried labor.

The finding that poorer households in Thailand derive a relatively large share of their income from holdings of pigs, cows, and buffalo implies that this is not a dimension along which their income choices are constrained. This is in contrast to Dercon (2002) and Dercon and Krishnan's (1996)

TABLE 3 Observable characteristics of households with below- and above-median permanent income

Level of permanent income	Below median	Above median	*t*-Statistics
Primary contract type of head (%)			
Government work	0.24	4.03	−12.13***
Other monthly salaried work	1.15	4.92	−9.720***
Daily wages	17.86	10.50	11.76***
Piece rates	1.32	1.80	−1.2455
Business owner	59.84	68.02	2.5312***
Other	0.16	0.35	−1.502
Decade of birth of head (%)			
1930s	26.05	14.45	13.95***
1940s	23.51	18.51	5.870***
1950s	22.65	37.22	−15.40***
1960s	13.49	21.62	−10.27***
Education level of head (%)			
Less than primary	21.82	9.73	16.08***
Primary	75.88	76.50	−0.7018
More than primary	2.28	13.77	20.66***
Other characteristics			
Head holds multiple jobs (%)	58.60	71.27	−12.40***
More than one breadwinner (%)	62.68	64.74	−3.461***
Any salaried income (%)	11.51	31.45	−23.90***
Headed by women (%)	36.14	24.54	12.09***
Involved in agriculture (%)	90.30	91.20	−2.318**
Lagged log of assets	9.73	11.10	−31.44***
Share of household income (%)			
Rice farming	31.13	26.32	6.580***
Livestock (pig, cow, and buffalo)	6.68	5.53	3.37***
Salaries	5.73	15.46	−19.52***

Notes: Each *t*-statistics presents the result of a difference in means test between the preceding columns.

$^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

findings in Tanzania and Ethiopia that the poor are excluded from rearing large livestock. This empirical evidence suggests that relatively poor households in middle-income countries face different constraints from their counterparts in poorer contexts and may help explain why I observe a markedly different distribution of income risk in this sample than in studies conducted in poorer contexts.

5 | ESTIMATING THE EFFECT OF A COVARIATE SHOCK ON INCOME

This paper tests for differences across the income distribution in the degree to which household income is insured against risk in a middle-income context. Identification requires an exogenous source of variability in the incomes of different households. To this end, I conceptualize household income as being composed of the following components:

1. A long-term component, $\bar{y}_i$, which is a function of structural household characteristics such as education and year of birth of the head of household
2. Fixed, village-level characteristics, $\bar{y}_v$, such as soil fertility and distance to the nearest city
3. A transitory, household-specific component, y_{it}
4. Village-level shocks, y_{vt}, such as the occurrence of a drought

The observed income of household i in village v at time t, which I denote by y_{ivt}, is given as follows:

$$y_{ivt} \equiv \bar{y}_i + \bar{y}_v + y_{it} + y_{vt} + \varepsilon_{ivt}, \tag{1}$$

where ε_{ivt} is a mean zero error term.

The long-run level of household $i's$ income, $\bar{y}_i$, is determined by that household's "innate" characteristics. In the empirical work, these include the characteristics of the head of household, such as the decade of birth cohort, sex, level of education, and whether the head is in salaried employment. They also include the stock of assets owned by the household, including land (both agricultural and homestead), household assets (truck, car, bicycle, gas stove, washing machine, telephone, television, etc.), agricultural assets (tractors, sprinklers, threshing machines, etc.), and business assets (machinery, inventory, buildings, etc.). Although such assets will clearly contribute to the productive capacity of the household and so should be included in a model of its longer-term income prospects, they may also be used as buffer stock and run down or built up in response to short-term income shocks. Therefore, in the empirical work that follows, the lag of the asset aggregate is used to model long-run income. The number of household members is also included as an explanatory variable to sweep up any scaling effects that are not captured by equivalence scaling. A dummy variable for whether the household is involved in agriculture is also included. Any remaining time-invariant heterogeneity across households is addressed using household fixed effects. Naturally, these fixed effects also subsume any time-invariant heterogeneity across villages, $\bar{y}_v$, for example, if some villages are more fertile than others or better connected to urban centers.

The transitory, household-specific component of income, y_{it}, will, in principle, include shocks to household income such as involuntary unemployment and waves of illness. However, as discussed earlier, the likelihood that a household is subject to these shocks will vary systematically with household characteristics such as wealth, human capital, occupation choice, and housing choice, which also predict permanent income. Thus, they do not provide suitable shocks for the current paper that identifies differences in income risk across the distribution of household permanent income.

Observed y_{it} will also include endogenous household responses to unanticipated decreases in income. There is a large literature on "the added worker effect" (Mincer, 1962) where the presence of an adverse shock to household income causes an increase in the labor supply of household members who do not otherwise provide labor to the market. Households may also respond to temporarily low returns to labor in one market by taking on additional work in another (Kochar, 1999).

In this context, it may also not be feasible to separate y_{it} from the error term, ε_{ivt}, because of measurement error and unobserved heterogeneity. If measurement error is independently and identically normally distributed across households, and over time, and "shocks" are used as explanatory variables (as they will be here), these errors decrease the efficiency of estimates. If, however, they are systematically related to any variable of interest (e.g., if richer households are more likely to underreport their income), then estimated coefficients will be biased and inconsistent. Insofar as unobserved heterogeneity is time invariant, the fixed effects strategy utilized here would remove the effect of this potential bias. But if heterogeneity varied over time, for example, if poorer households were more likely to receive "gifts" during lean times than their wealthier counterparts, y_{it} and ε_{ivt} would be correlated. Furthermore, the uniquely long-running panel data utilized here do not collect information on health or weather shocks at the household level. Given these credible threats to identification and the available data, it is not feasible for the current paper to identify exogenous shocks to household income in this context.

The empirical results that follow will focus on the village-level transient component of household income, y_{vt}, in Paxson (1992). As discussed in Section 3, the key informant interviews performed by the Townsend Thai Project allow me to compute the proportion of households in each village affected by a drought in each year. This variable allows the paper to identify an exogenous source of variation in the income streams of the cluster of households within a specific village while circumventing some of the sources of bias that may result when individual households self-report shocks (discussed earlier). Nevertheless, this variable is based on the perceptions of the village head, so the possibility of some reporting error remains. Any such error, however, will manifest at the village level, whereas identification focuses on variation between households and over time. The paper further assures against village-level reporting errors by conducting sensitivity analysis that explicitly accounts for village fixed effects. Sensitivity analysis also includes specifications and regional trends which would pick up any linear or quadratic changes in the reporting errors across regions. Furthermore, the prevalence of drought is used as a right-hand side variable so that any measurement error would, if anything, attenuate the results.

The focus on a covariate shock is also supported by previous work that has demonstrated that households in this setting are able to pool risks and so enjoy effective insurance against household-level shocks. This work has demonstrated that village-level shocks continue to adversely affect the welfare of sampled households as these cannot be mitigated by risk sharing (Chiappori et al., 2011; Samphantharak & Townsend, 2018). Earlier work (Felkner et al., 2009) has also projected that high-emission climate-change scenarios will reduce rainfall availability to the detriment of particular poorer households. This provides a further impetus to study the distributional effect of drought on income risk among Thai households.

5.1 | Does drought affect village income?

5.1.1 | Ordinary least squares estimates

The analysis discussed earlier has demonstrated that income portfolios in this context are much more diversified than in an earlier work on heavily agrarian samples. Therefore, this paper must empirically determine whether the prevalence of drought causes transient decreases in village income in this sample. To this end, I model the effect of the proportion of households in village v that are affected by a drought in year t, d_{vt}, on the incomes of households in that village cluster in that year, y_{ivt}. Thus, to model the effect of drought on village incomes, I estimate the following equation:

$$y_{ivt} = \alpha_i + \beta' X_{it} + \delta d_{vt} + \tau t + e_{ivt}, \tag{2}$$

where α_i is the household fixed effect, X_{it} is a set of household characteristics, d_{vt} is the drought variable described earlier, t is the time trend, and e_{ivt} is a mean zero error term. β, δ, and τ are parameters to be estimated. In addition to drought, I condition on the number of household members in employment,

TABLE 4 The mean effect of drought on income

	(1)	(2)
	OLS	**2SLS**
Drought	−0.000941***	−0.00113***
	(−3.17)	(−3.65)
Head has more than one job	0.0669**	0.0398
	(2.51)	(0.39)
Employment rate within household	0.250***	0.240**
	(4.57)	(2.44)
Constant	9.414***	9.310***
	(35.43)	(35.84)
N	8,289	7,699

Notes: In all specifications, the dependent variable is the log of real equivalized net household income. All specifications include dummy variables for whether the head has more or less than a primary education (the omitted category is the head is educated to the primary level), the sex of the head of household, the lagged log of assets, whether the head earns a monthly salary in his or her main occupation, household size, decade of birth cohort of the head of household, a time trend, and household fixed effects. Standard errors are clustered at the village level. The first specification enters "head has more than one job" and "employment rate within the household" contemporaneously, while the final specification instruments for these values using two lags of each of these endogenous variables. *t*-Statistics are in parentheses.

OLS, ordinary least squares; 2SLS, two-stage least squares.

*$p < .10$; **$p < .05$; ***$p < .01$.

the number of jobs taken on by the head of household, the level of education of the head of household, a cohort effect for the decade of birth of the head of household, the primary occupation of the head of household, household size, the lag of household asset endowments, and whether the household is involved in agriculture.[5]

The first column of Table 4 presents the results of this regression. The coefficient on the variable for the proportion of households in each village affected by drought is negative and has a reasonable magnitude: at the sample mean, a 10-percentage point increase in the proportion of households affected by drought decreases the real, equivalized income of the mean household in that village by 0.9%.[6]

5.1.2 | Two-stage least squares estimates

The effect of drought on the income streams of these households is potentially confounded in the data by endogenous household responses to these shocks, which may cause ordinary least squares (OLS) estimates to be biased and inconsistent. As households are not passive recipients of this village-level shock, they may respond with added worker effects and labor substitution to alternative income-generating activities (Kochar, 1999; Mincer, 1962). As these variables are likely to be positively correlated with both household income and the onset of drought, the OLS estimates of the effect of drought on income would be biased toward zero. A similar argument applies to the number of household members in employment.

I therefore use two lags of these potentially endogenous variables to instrument for their contemporaneous values in a two-stage least squares (2SLS) estimation strategy. For this strategy to be effective, the lags need to be highly correlated with the contemporaneous values but uncorrelated with the materialization of drought. It is intuitive that these variables will be strongly correlated with their lags (as the following F-tests confirm). In this application it is also reasonable to assume that the lagged values of these labor supply variables will not be correlated with drought, as households cannot know 1 or 2 years in advance if a drought will occur.[7] Proceeding by using two lags of the potentially endogenous variables as identifying instruments for their current values in the first stage, the second-stage equation may be written as follows:

$$y_{ivt} = \alpha_i + \beta' X_{it} + \theta'^{\widehat{x_{it}}} + \delta d_{vt} + \tau t + e_{ivt}, \tag{3}$$

where $\widehat{x_{it}}$ denotes the instrumented variables and the θ's are parameters to be estimated.

The resulting model passes the usual diagnostic tests for relevance and exogeneity. The first-stage F-statistic for the head holding more than one occupation is 12.8, whereas that of the employment rate within the household is 111.5.[8] Though using two lags as identifying instruments reduces the sample size (so that effectively Equation 3 is estimated on only 13 years of data from 1999 to 2011), the advantage of doing so is that it allows the computation of an overidentifying restrictions test. An overidentifying restrictions test yields a χ^2 value of 0.589 that is distributed with two degrees of freedom. Thus, the null hypothesis that the model is correctly specified is upheld.

The second column of Table 4 presents these 2SLS results. There is a sharp decrease in the point estimate on the labor substitution variable that is no longer statistically significant, whereas the estimated coefficient for added worker effects remains largely unchanged. The estimated coefficient of drought on income increases in magnitude, so that a 10-percentage point increase in the share of households affected by drought decreases real income per adult equivalent by 1.1%.

5.2 | Are the incomes of the well-off better insured against drought?

I now extend the model to answer the key research question of this paper, that is, Are the income streams of better-off households less sensitive to the reported covariate shock?

I adopt a reduced-form approach to answering this question by interacting drought with measured permanent income, defined earlier. This frames the problem as a moderated relationship (Aiken & West, 1991; Jaccard & Turrisi, 2003) where I test if the effect of drought on income is moderated by permanent income. The identifying assumption is that in the absence of different insurance strategies, households across the income distribution in each cluster would, on average, have suffered similar proportionate losses in income if that cluster were affected by drought. Of course, these results should not be interpreted as a causal effect of high permanent income on income risk but rather as an attempt to test whether an economically meaningful correlation exists.

In the following empirics, I follow the textbook advice (Jaccard & Turrisi, 2003) and subtract the mean value of $\bar{c}_i$ over the entire sample from each household's estimated permanent income so as to ease interpretation. That is, I define the quantity

$$\bar{c}_{\mu i} = \bar{c}_i - \mu, \tag{4}$$

where μ is the average $\bar{c}_i$ observed in the sample. I estimate

$$y_{ivt} = \alpha_i + \beta' X_{it} + \theta' \widehat{x_{it}} + \delta d_{vt} + \chi \left(d_{vt} \times \bar{c}_{\mu i} \right) + \tau t + e_{ivt}, \tag{5}$$

where the remaining terms are as defined earlier. As before, I account for the potential endogeneity of the number of jobs held by the household head and the employment rate within the household using an instrumental variables strategy.

If the income streams of households with higher levels of permanent income are better insured against covariate shocks, χ will be positive and significant. The first column of Table 5 presents the results. The coefficient on the interaction term, χ, is positive and different from zero at all conventional levels of statistical significance so that the adverse effect of drought on income is indeed moderated by high levels of permanent income. The magnitude of the coefficient is such that at the sample mean, a one standard deviation increase in mean consumption (0.459 log points) nullifies the impact of drought on income.

These results are corroborated when I split the sample into households with permanent income above or below the sample median and reestimate Equation 3, as presented in the second and third columns of Table 5, respectively. Column 2 shows that there is no statistically significant effect of drought on income for households whose permanent income is above the sample median, whereas the third column confirms a significant and large negative effect of drought for relatively poor households.

Given that the focus of this paper is on inequalities across the distribution of household income, the median is a natural choice of sample split. Nonetheless, it is important to acknowledge the somewhat arbitrary nature of any single choice of split and to insure that the result is not unduly sensitive to this choice. For this reason, the remaining columns of Table 5 present the estimates of the effect of drought on income where the sample is split at the 40th and 60th percentiles. Regardless of the choice of split, the point estimate on the coefficient of drought for relatively rich households is at most approximately half that of the entire sample and never statistically different from zero at the 1% level. By contrast, the point estimate for the effect of drought on income for relatively poor households is always substantially larger than the sample average and always significant at the 1% level.

These results, though reassuringly consistent, make restrictive assumptions about the distributional effect of drought: Equation 5 assumes it is log-linear in permanent income, and the sequence of sample splits assumes that heterogeneity is distributed in a binary manner across groups. Quantile regressions (Koenker & Bassett, 1978) require no such a priori distributional assumptions. However, such flexibility comes at a cost: currently there are no widely accepted statistical techniques that allow for the computation of consistent instrumental variables estimates and their standard errors by quantiles.[9] As such, it is not possible to consistently reestimate Equation 3 by quantiles. Instead, I estimate quantile regressions for versions of Equation 2.

Figure 7a presents the point estimates and confidence intervals for δs that result from estimating Equation 2 with the full set of explanatory variables by quantiles with fixed effects (Machado & Santos Silva, 2019). The results suggest that the income streams of households in the top 20% of the distribution of permanent income are insulated from the effect of drought. Drought exerts a significant negative effect on income for the rest of the distribution, with the effect size becoming more severe for poorer households. A concern resulting from this specification is that the contemporaneous values of the employment rate within the household and the number of jobs held by the head may be "bad controls" (Angrist & Pischke, 2009) so that the estimated effects of drought on income may be biased upward (i.e., toward zero) as explained earlier. The alternative approach implemented in Figure 7b estimates the effect of drought by quantiles but having dropped these potential "bad controls" so as to retrieve consistent estimates of the drought effect. I again find no statistically significant effect of drought on the income streams of the most well-off 20% of households, whereas drought exerts a negative, statistically significant effect on household income for the remainder of the distribution. As in Figure 7a, the effect becomes severely low in the income distribution.

Thus, relatively well-off households in rural Thailand enjoy income streams that are better insured against this covariate shock.

TABLE 5 2SLS estimates of heterogeneous effects of drought on contemporaneous log income by level of permanent income

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Permanent income moderates the effect of drought	**Households with above median permanent income**	**Households with below median permanent income**	**Households above 40th percentile of permanent income**	**Households below 40th percentile of permanent income**	**Households above 60th percentile of permanent income**	**Households below 60th percentile of permanent income**
Drought	−0.00123***	−0.000586	−0.00172***	−0.000681**	−0.00196***	−0.000129	−0.00194***
	(−4.56)	(−1.63)	(−4.19)	(−2.03)	(−4.88)	(−0.033)	(−5.32)
Drought × permanent income	0.00232***						
	(4.47)						
Constant	9.296***	9.568***	8.948***	9.554***	8.872***	10.048***	9.312***
	(35.75)	(23.23)	(30.11)	(26.55)	(27.18)	(24.80)	30.89
N	7,699	3,950	3,749	4,756	2,943	3,172	4,527

Notes: In all specifications, the dependent variable is the log of real equivalized net household income. All specifications include dummy variables for the head of household having less than a primary education, the head of household having more than a primary education (educated to primary level is the base category), the head of household being in a form of employment that pays a monthly wage, the household being involved in agriculture, the sex of the head of household, a set of cohort fixed effects, and a set of household fixed effects. Continuous regressors for the lagged log of assets, household size, and time are also present. Standard errors are clustered at the village level. As in the second column of Table 4, lags of "head has more than one job" and "employment rate within the household" are used as identifying instruments to address the endogeneity of these variables to the onset of drought. *t*-Statistics are in parentheses.

2SLS, two-stage least squares.

*$p < .10$; **$p < .05$; ***$p < .01$.

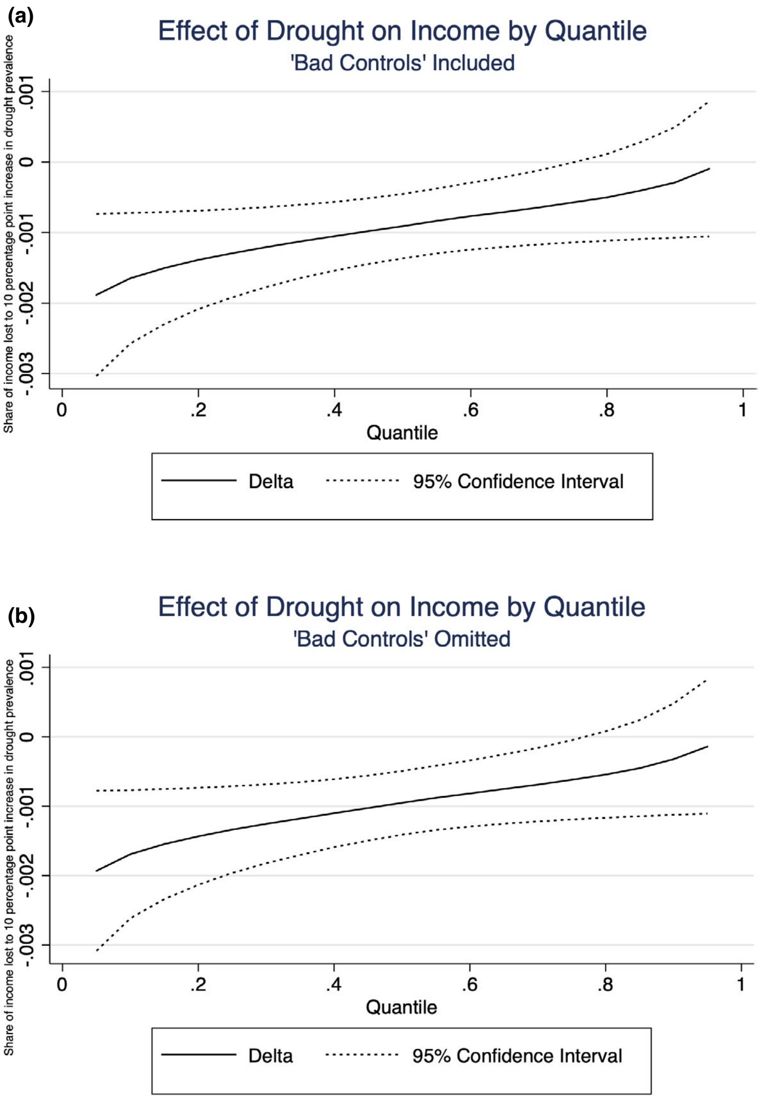

FIGURE 7 (a) Effect of drought on income by quantile, "bad controls" included. (b) Effect of drought on income by quantile, "bad controls" omitted

5.3 | The effect of drought by households' observable characteristics

Table 3 illustrated that households with above-median permanent income were, on average, more likely to be headed by people in salaried jobs, who were better educated, who were younger, and who were based in the central region compared to those households with below-median permanent income. To understand if any of these differences are empirically related to the ability of households to insure their income streams against drought, I reestimate Equation 3 on groups of households that exhibit each of these characteristics.

The first column of Table 6 restricts attention to those households that are headed by people in government work or other jobs that pay monthly salaries. Perhaps unsurprisingly, the estimated coefficient for drought in this subsample is statistically indistinguishable from zero. Even though these households are disproportionately drawn from among the better-off (evidenced in Table 3), this result

TABLE 6 Effect of drought on log income by household characteristic

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Subgroup	**Monthly salary: Head**	**Monthly salary: Any member**	**Head more than primary education**	**Head born in the 1930s**	**Head born in the 1940s**	**Head born in the 1950s**	**Head born in the 1960s**	**Central region**	**Northeastern region**	**Rice farmers**
Drought	−0.00132	−0.000636	−0.00131	−0.00226***	−0.000922	−0.000710*	−0.000791	−0.000148	−0.00215***	−0.00143***
	(−1.06)	(−1.22)	(−1.39)	(−3.90)	(−1.38)	(−1.80)	(−1.11)	(−0.43)	(−5.47)	(−3.81)
Cohort fixed effects	Yes	Yes	Yes	No	No	No	No	Yes	Yes	Yes
Constant	10.83***	11.03***	10.08***	9.533***	9.440***	9.717***	10.01***	9.493***	9.361***	9.089***
	(10.16)	(24.74)	(12.43)	(15.91)	(19.03)	(24.14)	(14.71)	(16.50)	(32.65)	(25.54)
N	410	1,728	664	1,520	1,612	2,379	1,389	3,460	4,239	4,461

Notes: All specifications include dummy variables for the "head has more than primary education," "head has less than primary education" (educated to primary level is the base category), "head earns monthly salary," "household is involved in agriculture," and a set of household fixed effects. Continuous regressors for the lagged log of assets, household size, and time are also present. Standard errors are clustered at the village level. As in Table 4, lags of "head has more than one job" and "employment rate within the household" are used as identifying instruments to address the endogeneity of these variables to the onset of drought. t-statistics are in parentheses.

$^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

is of only limited use in explaining the overall distribution of income risk as it applies to just 5.2% of the sample (furthermore, nonrejection may be due to the reduced sample size). The second column of Table 6 tests if the result generalizes to the case where a household in a particular year derives any income at all from monthly salaried work. This much-broader group includes 11.5% of relatively poor households and 31.5% of relatively well-off households. The estimated coefficient of drought on income among households that have access to salaried jobs is roughly half the size of that for the overall sample and statistically indistinguishable from zero at conventional levels. Thus, salaried jobs appear to constitute an important channel through which richer households are insured against income risk.

Tellingly, in the subgroup of households headed by people who earn monthly salaries, no household heads with less than a primary education were observed. This indicates that the income streams of better-off households may be better insulated against shocks, in part, because their endowments of human capital enable them to access jobs with low income risk. The results in the third column substantiate this hypothesis by restricting attention to households where the head has completed an educational qualification greater than the primary level, that is, one of secondary, university, or vocational degrees. The effect of drought on the income streams of these households is also statistically indistinguishable from zero. Households with above-median permanent income are more than six times as likely to be headed by people with these high levels of education than households with below-median permanent income, as was documented in Table 3.

The fourth to seventh columns of Table 6 restrict the sample to households that are headed by people born in the 1930s, 1940s, 1950s, and 1960s, respectively. Drought has a statistically significant, large, negative effect only on the income streams of households headed by the eldest of these cohorts. For households headed by cohorts born after 1940, the estimated effect of drought is never significantly different from zero at the 5% level. The data thus suggest that households headed by people born after 1940 are better able to adapt to covariate shocks. This may be because younger cohorts are better equipped to access information on changing market conditions, and they may have human capital such as information technology skills that enable them to better respond to such changes. Alternatively, the heads of richer households may self-select into early retirement, leaving such households with younger heads. If households with younger heads enjoy inherently better insurance possibilities, this form of selection may also be an important mechanism underpinning this result.

The eighth and ninth columns of Table 6 allow for drought to affect village households differently in central and northeastern villages, respectively. In the relatively affluent central region, the presence of drought does not exert a statistically significant effect on household income. In contrast, the presence of a drought exerts a strong, negative effect on household income in the relatively poor and semiarid northeastern region. Thus, there is some evidence that geographic factors, perhaps soil quality and rainfall variation, but also potentially a lack of proximity to urban centers, may constrain the ability of relatively poor households to generate low-risk income.

A robust finding of the income smoothing literature from poorer, exclusively agrarian contexts is that differences in the share of specific crops in household income portfolios are likely to be a key driver of this type of smoothing (Dercon, 2002; Morduch, 1995; Rosenzweig & Binswanger, 1993). Rice is the single most important crop in the Thai context, with the proceeds from rice farming accounting for, on average, 31.1% and 26.3% of the net incomes of relatively poor and rich households, respectively (Table 3). The 10th column of Table 6 presents the estimated effect of drought on income for the 58% of sample households that farm rice. At the 5% significance level, this coefficient is not significantly different from that obtained for the whole sample (t-statistics: 0.606), nor is it significantly different from the analogous coefficient for households that do not farm rice (t-statistics: 1.65). Thus, despite the increased prevalence of rice farming among the relatively poor, there is not much strong evidence relating rice farming to the insurance possibilities available to these households.

Income from other crops recorded in this data set constitutes very small fractions of household income, as noted in footnote 4, and so does not explain the aggregate distribution of income risk.

Table A1 presents further heterogeneity analysis of the effect of drought on household income by restricting attention to business-owning households, female-headed households, households where the head has more than one job, households where there is more than one breadwinner, and households that report being involved in at least some form of agriculture. Though some of these factors were found to have been important correlates of income risk in poorer settings than the current data set, the degree to which drought affects the income streams of all these subgroups is similar to the result for the whole sample and so is not informative of differences in exposure to income risk.

5.4 | Sensitivity analysis

5.4.1 | Regional trends

The analysis so far has assumed that the long-term trends in the data-generating process are similar across the different regions covered in the sample. This is a strong assumption given the regional variation that has been documented in a variety of studies using the Townsend Thai data, including in relation to access to credit, changes in price levels, dependence on remittances, barriers to trade, and exposure to climate change (Felkner et al., 2009; Paulson & Townsend, 2004; Pawasutipaisit & Townsend, 2011; Samphantharak & Townsend, 2018; Townsend, 2013). To allow for systematic differences in the evolution of economic forces between regions, I reestimate Equation 5, including region-specific linear time trends. The results are presented in the first column of Table 7 and should be compared to those in the first column of Table 5. The coefficient on drought remains very similar in magnitude and statistically significant, as does the main coefficient of interest, the interaction between drought, and household permanent income. This result is also robust to the inclusion of region-specific quadratic trends, as reported in the second column of Table 7. Thus, it does not appear to be the case that the main results of these papers are driven by differences in inflation rates, other long-term economic differentials, or differential effects of climate change between regions.

5.4.2 | Equivalence scales

The use of any given equivalence scale makes an implicit assumption about the nature of economies of scale within households. At one extreme, the simple per-capita adjustment assigns a weight of 1 to each individual in the household and so assumes that there are no economies of scale in household consumption. Though this adjustment is frequently used, the assumption it implies is clearly a very strong one. In contrast, the scale proposed by Hagenaars et al. (1994) (also known as the "new OECD scale") assumes fairly strong scale effects by assigning a weight of 1 to the first member, a weight of 0.5 to each additional adult member, and a weight of 0.3 to each child. The preferred scale used throughout this paper is the "old OECD" (OECD, 1982) scale, also known as the Oxford scale, and it specifies a degree of scale effects that is between the previous two, assigning a weight of 1 to the first household member, a weight of 0.7 to each additional adult, and a weight of 0.5 to each child. Rather than make an ad hoc assumption about the nature of scale economies within Thai village households, the third and fourth columns of Table 7 test if the main empirical result of this paper—that richer households have income streams that are better insured against drought—is robust to the use of the

TABLE 7 Sensitivity analysis

	(1)	(2)	(3)	(4)	(5)	(6)
	With region-specific linear time trends	**With region-specific quadratic time trends**	**Using the "New OECD" scale**	**Using the per-capita scale**	**Instrumental variables village fixed effects**	**Instrumental variables random effects**
Drought	−0.00126***	−0.00126***	−0.00121***	−0.00124***	−0.00120***	−0.00119***
	(−4.70)	(−4.86)	(−4.46)	(−4.55)	(−4.50)	(−4.35)
Drought × permanent income	0.00225***	0.00212***	0.00238***	0.00225***	0.00260***	0.00248***
	(4.41)	(4.06)	(4.48)	(4.30)	(4.18)	(4.86)
Constant	9.294***	9.378***	9.543***	9.044***	9.148	9.110
	(35.41)	(36.97)	(36.75)	(34.89)	(42.05)	(44.67)
N	7,699	7,699	7,699	7,699	7,699	7,699

Notes: All specifications include a constant term, dummy variables for the head of household having less than a primary education, the head of household having more than a primary education (educated to primary level is the base category), the head of household being in a form of employment that pays a monthly wage, the household being involved in agriculture, the sex of the head of household, and a set of birth cohort of head effects. All specifications except (5) contain household fixed effects. Continuous regressors for the lagged log of assets, household size and time are also present. Standard errors are clustered at the village level. Lags of "head has more than one job" and "employment rate within the household" are used as identifying instruments to address the endogeneity of these variables to the onset of drought. *t*-Statistics are in parentheses.

*$p < .10$; **$p < .05$; ***$p < .01$.

TABLE 8 Characteristics of panel and attritted households in 1997

	Panel households ($N = 609$)	Attritted households ($N = 347$)	t-Statistics
Proportion of households			
Head earns monthly salary	0.0575	0.0634	0.3719
Head highly educated	0.0377	0.0634	1.8007
Head born in the 1930s	0.235	0.199	−1.29
Head born in the 1960s	0.143	0.182	1.58
Northeastern region	0.553	0.401	−4.32***

Notes: The t-statistics present the result of a difference in means test between households that are subject to attrition from the sample from 1998 to 2011 and those that are successfully reinterviewed in every period.

*$p < .10$; **$p < .05$; ***$p < .01$.

"new OECD scale" and the per-capita scale, respectively. They are, as the point estimates are virtually unchanged under different scales and the coefficients continue to be highly statistically significant.

5.4.3 | Village fixed effects and household random effects models

The results presented so far have relied heavily on models with a full set of household fixed effects. Column 5 of Table 7 relaxes the parameterization to include village- instead of household fixed effects. Again, the estimated effect of drought and the interaction between permanent income and the incidence of drought remain largely unaffected. Thus, the key result of this paper is preserved in this relatively parsimonious parameterization.

Though the fixed effects model is useful in assessing the sensitivity of the results to time-invariant heterogeneity, it exploits only variation within but not between households. In this regard, the random effects estimator may provide important supplementary information with possible increases in efficiency. The sixth column of Table 7 presents these results. Again, the key coefficients remain largely unaffected.

5.4.4 | Sample attrition

The main results of this paper are based on the balanced panel of 609 households that are interviewed by the Townsend Thai Project every year from 1997 to 2011 without any missing or obviously spurious values recorded for income and consumption in these periods. If households that are less able to cope with shocks are at heightened risk of exiting the panel, attrition may affect the estimates. Table 8 compares the 347 households that were interviewed from these villages in 1997 but were subject to attrition at some point over the duration of the panel to the 609 households that comprise the balanced panel, over the characteristics (observed in 1997) that the current analysis has found to be related to the ability of households to cope with risk.

Contrary to the foregoing concerns, households that are subject to attrition are more likely to be headed by someone who earns a monthly salary in 1997 than households that are not. A similar narrative emerges for the level of education of the head of household, whereby the highly educated are overrepresented among households that are eventually subject to attrition. Attritted households also appear to be less likely to be headed by someone from an earlier cohort, a result that also runs contrary to the concern that attrition is higher among at-risk households. More important, none of these differences in contact type, education level, and birth cohort are statistically significant at the 5% level.

The final row of Table 8 presents the likelihood of attrition among households sampled from the semiarid northeastern region. These results show that households from this relatively poor region are actually less likely to be subject to attrition. While the difference is statistically significant, the result is contrary to the concern that poorer households are more likely to drop out of the panel.

6 | CONCLUSIONS

This paper has studied heterogeneity in income risk between households in rural Thailand across the income distribution. The finding that the income streams of relatively well-off households are better insured against covariate shocks is a novel contribution in the literature on income risk, which has usually focused on identifying income-risk mitigation strategies among the relatively poor and vulnerable in exclusively agrarian settings in South Asia. In contrast to this earlier literature (but consistent with Gutierrez's, 2014, more recent findings from Mexico, another middle-income country), among the more diverse income portfolios of rural Thai households, low-risk income is associated with human capital and the ability to take up salaried employment.

The results suggest that in rapidly industrializing parts of the world, particular attention should be paid to evaluating the impact of increasing access to jobs that pay monthly salaries. These jobs have the potential to contribute to household welfare not only by increasing average earnings but also by serving an important insurance function. This insurance function is likely to benefit households that are able to secure these high-return low-risk opportunities. However, to the extent that these opportunities are restricted to the relatively well-off who are more likely to be younger, well educated, and living close to urban hubs, they may have adverse distributional consequences. Furthermore, if climate change were to increase the incidence and severity of covariate risks such as drought, these results suggest that the direct welfare loss will be borne disproportionately by relatively poor members of these communities who lack access to low-risk income-generating opportunities.

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DATA AVAILABILITY STATEMENT

The data that support this study are openly available at "The Harvard Dataverse" at https://dataverse.harvard.edu/dataverse/rtownsend.

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ENDNOTES

[1] Section 5.4 includes sensitivity analysis that insures that the key results of this paper are not driven by attrition from the sample.

[2] Section 5.4 checks that the key results of this paper are not unduly sensitive to the choice of equivalence scale.

[3] In question VH8B of the “Key Informant Annual Resurvey” (The Townsend Group, 1998–2011) after reading out a list of potential shocks, the enumerator asks the informant, “Approximately how many households in the village were affected by this event?” This information is combined with the answers to question VH2A, which asks, “How many households are there in this village today?” to compute the proportion of households affected by drought in each village.

[4] The mean proportion of household income from corn farming is 2.9%, from vegetables is 1.4%, and from orchards is 2.4%. These are the only other specific sources of crop income that are recorded in the data set. As they constitute very small fractions of net household income, they do not explain the overall distribution of income risk.

[5] The distribution of these variables across the sample was described in Section 4 and is presented in Table 3.

[6] Although key informants are selected for interview in part because they have specialist knowledge of the context, it is important to acknowledge that even data gathered by this method are not immune to measurement error. Nonetheless, as the drought variable is used as an independent variable, the presence of measurement error would bias the coefficient toward zero and so work against us.

[7] If climate change increased the occurrence of drought, then the frequency with which households place additional members on the labor market or substitute labor to off-farm activities would increase, leading to an increase in the bias on the OLS estimate of the effect of drought on income. However, provided the onset of drought in a particular year cannot be predicted ex ante, the current instrumentation strategy would identify consistent estimates of the drought parameter.

[8] Each is distributed with (21, 63) degrees of freedom, so the null hypothesis that the instruments are unrelated to endogenous regressors is resoundingly rejected.

[9] Though the Abadie et al. (2002) estimator is readily implemented using the contributions of Frölich and Melly (2010), this strategy is suitable only where the treatment variable is dichotomous.

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APPENDIX

TABLE A1 Effect of drought on log income by household characteristic

	(1)	(2)	(3)	(4)	(5)
Subgroup	**Head is business owner**	**Female head**	**Head has multiple jobs**	**Multiple earners in household**	**Involved in agriculture**
Drought	-0.00128^{***}	-0.00106^{**}	-0.00122^{***}	-0.00108^{***}	-0.00125^{***}
	(−3.57)	(−2.08)	(−3.43)	(−3.05)	(−3.85)
Constant	9.113^{***}	8.657^{***}	9.272^{***}	9.301^{***}	9.406^{***}
	(20.50)	(22.01)	(23.84)	(30.04)	(31.75)
N	4,930	2,319	5,071	6,749	6,988

Notes: All specifications include dummy variables for the "head has more than primary education," "head has less than primary education" (educated to primary level is the base category), "head earns monthly salary," "household is involved in agriculture," a set of household fixed effects, and a set of cohort fixed effects. Continuous regressors for the lagged log of assets, household size, and time are also present. Standard errors are clustered at the village level. Lags of "head has more than one job" and "employment rate within the household" are used as identifying instruments to address the endogeneity of these variables to the onset of drought. *t*-Statistics are in parentheses.

$^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.